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Does climate risk drive digital asset returns?

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A B S T R A C T

This research employs quantile-on-quantile regression and the quantile coherency method to examine the asymmetric effects of various climate-related risks (physical and transition) across different states (from high to low) on digital assets, including the returns from cryptocurrencies, non-fungible tokens (NFTs), and decentralized finance (DeFi). The findings indicate that climate-related risks negatively affect the returns of cryptocurrencies, NFTs, and DeFi assets in the upper quantiles, meaning that these risks reduce returns. Conversely, in the lower quantiles their impact is inverse, highlighting the asymmetric influence of climate-related risks on cryptocurrencies, NFTs, and the DeFi market.

1. Introduction

Like any other traditional financial assets, digital assets are also exposed to climate risks [1,2]. To a certain extent, climate change and digital assets are inherently linked together, because as the adoption of high-carbon footprint digital assets increases, climate change intensifies [2–4]. Furthermore, with climate-related risks, the digital world is vulnerable to disruption, regulatory scrutiny, and market volatility. Thus, the connection between climate and digital assets can be seen as a dual and challenging mechanism with no obvious solution that does not involve some form of detriment. Is this scenario truly the case? While the literature has examined the adverse effects of digital asset usage on the environment, highlighting energy consumption and carbon emissions from mining and transaction processes [2,4–7], the impact of intensifying climate risks on digital assets remains understudied. As market participants increasingly integrate climate-related considerations into their decision-making processes, understanding the causal effects of climate

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risks on digital assets becomes crucial for risk management, portfolio allocation, and investment strategies. Hence, with this paper we shall explore the linkage between climate-related risks and digital assets, offering insights for investors, regulators, and policymakers to govern this complex landscape more effectively.

The emergence of blockchain-based assets characterizes a transformative change in financial markets [8–11]. Speculative and hedging opportunities associated with these assets [12,13][1] enable accessible digital transaction-level information and have attracted the attention of market participants. However, the energy consumption and carbon footprint levels of digital assets are of particular concern in today's world. In fact, the urgent need for collective mitigation actions from governments, institutions, and individuals (e.g., abating human-caused greenhouse gas (GHG) emissions and reducing the use of resources) is essential to containing the adverse effects of today's changing climate. Thus, unregulated carbon emissions resulting from digital assets-related activities might pose serious threats to the achievement of global climate targets, especially considering the expected growth of this market. Their heavy dependence on energy and electricity, coupled with high emission levels, undermine the climate transition paths of financial market participants who have invested in these digital assets.

Uncertainties in the response of digital assets to intensifying climate-related risks can significantly impact risk assessments, as market participants fail to fully measure the exposure to climate change risks stemming from their digital asset holdings or properly ascertain if their digital or multi-asset portfolios are aligned with decarbonization trajectories, such as those outlined in the Paris Agreement. Due to the inherently global nature of digital assets, domestic regulatory efforts aimed at mitigating their environmental impact are insufficient as, in absence of cross-border coordination, negative externalities are simply shifted from one geographic location to another, while the overall adverse impact on the environment remains unchanged. From here, there is an increasing need to deepening our understanding of the intricate nexus between climate-related risks and digital assets so as to shed light on the risk transmission mechanisms between the two.

This paper provides empirical evidence on the impact of climate-related risks to the digital assets' market, specifically motivated by the rationale that shocks to climate risks can propagate to the digital market in the form of distressed reaction [14]. Given the high-volatile nature of digital assets, examining the effects of climate risks on extreme values of the return distributions should offer greater insights on the size of digital asset sensitivity to climate risks. Thus, our research seeks to document potential digital asset extreme responses to innovation to climate risks under various conditions by considering different climate risk components and different digital asset types. Finally, we ask: Are cryptocurrencies as a safehaven still true under high climate risks?

The theoretical linkage between digital assets and climate-related risks depends on the source of climate-related risk; i.e., physical or transition risks, as already demonstrated by how these climate risks impact the economy differently [15]. On one side, the former risks stem from the adverse impacts of acute climate events (like floods or heat waves) or chronic hazards (like sea level rise or drought) on vulnerable and exposed elements. On the other side, the latter risks arise from the process of adjustments toward a greener economy and society, usually prompted by climate and environmental policy changes, shifts in public preferences, and technological advances [16]. Thus, in the context of digital assets, climate physical-related risks, like heatwaves, might put pressure on, for example, electricity systems of blockchains in multiple ways, causing an increased risk of operational disruptions. In this regard, the effects of physical and transition risks on market volatility, investor confidence, and liquidity may explain how climate-related risks affect the digital assets return. Finally, the interdependence of the financial system amplifies the impact of climate-related risks on digital assets [17,18]. Such risks can spur systemic risks that affect a variety of digital assets and conventional financial assets [19], with the potential for creating uncertainty in the market. This can amplify market volatility and thereby impacting their returns.

Our empirical approach follows specific steps. First, we employ Sim and Zhou [21]'s Quantile-on-quantile regression (QQR) technique to assess the asymmetric impact of climate-related risks on cryptocurrencies, NFTs, and DeFi assets return. QQR is a more sophisticated version of Quantile Regression (QR) that incorporates non-parametric estimates alongside a regular QR technique. It combines conventional linear regression with the QR model to better understand the interactions between the dependent and independent variables, offering a suitable framework for our study. Our results suggest that lower (higher) climate transition risk increases (reduces) the return of cryptocurrencies, NFTs, and DeFi assets. This finding is attributed to digital assets mining's energy usage, with most of this energy coming from fossil fuels that contribute to climate change. The carbon footprint of digital asset mining may become a liability as TRI rises, leading to regulatory measures that could reduce the assets' values. Furthermore, as investors become more concerned about climate change, investor sentiment shifts toward low-carbon sectors. This shift has the potential to decrease demand for cryptocurrencies, NFTs, and DeFi assets with carbon-intensive mining processes. Our evidence of an asymmetric effect supports that of Ilhan et al. [22]. Second, we employ quantile granger causality and quantile coherency methods, which indicate an asymmetric effect of climate risk on the digital asset market.

Our study makes several important contributions to the growing body of literature on FinTech and sustainability, particularly through bridging the gap between climate risks and evolving digital asset markets. First, we extend the discourse on climate risks by applying it to digital assets, an area that has received only limited attention in previous research. Most earlier studies primarily focused on traditional assets, green assets, and commodities, leaving the implications of climate risks for digital assets largely unexplored [15, 23–27]. Our study addresses this gap by examining the relationship between climate risks - both physical and transition risks - and digital assets, including cryptocurrencies, NFTs, and DeFi assets. By investigating this underexplored domain, we offer novel insights into how environmental factors can influence the emerging world of digital finance.

[1] NFTs (non-fungible tokens) are digital assets representing ownership of unique physical or digital items, in which their information is stored on a blockchain, and are not interchangeable with other assets [10,11]. DeFi is a decentralized type of finance that operates on blockchain technology without the need for central financial intermediaries. DeFi uses smart contracts on blockchains to enable peer-to-peer transactions [12,13].

Second, while some prior studies have investigated the energy consumption and carbon emissions associated with cryptocurrency mining and transaction processes [4,5,7,28–30], our study contributes to this research stream in a unique way by focusing on how physical and transition climate risks directly affect digital assets. In this regard, we differentiate our study from prior studies by broadening the scope beyond energy consumption to explore the broader risks that climate change poses to the digital finance sector.

Finally, we employ the quantile-on-quantile regression (QQR) method, which allows us to explore the asymmetric impact of climate risks across the different quantiles of the return. Unlike traditional regression techniques, QQR enables us to identify how the impact of climate risks varies not only between digital asset classes but also across different market conditions, ranging from normal to extreme risk scenarios. This methodological approach provides valuable insights into the relationship between climate risks and digital assets, highlighting how such risks may manifest differently depending on the state of the market, something that is often overlooked in studies that rely on linear models.

The rest of the paper runs as follows. Section 2 discusses the approach. Section 3 presents the dataset. Section 4 discusses the empirical findings. Section 5 concludes the paper.

2. Background and related literature

The electricity consumption associated with Bitcoin by 2019 had surpassed that of several sizable nations like Norway, Sweden, and United Arab Emirates, positioning itself as the 27th largest consumer of electricity worldwide. In terms of GHG emissions, Bitcoin ranked 69th among all countries globally, and with 72.27 MtCO2e[2] emissions per year, Bitcoin's closest real-world industrial activity is gold mining.[3] Taking into account that these statistics focus solely on estimates for Bitcoin, it is worth noting that a substantial 48.3 % of the digital asset market is not included in these figures,[4] raising further concerns regarding the overall energy consumption and greenhouse gas (GHG) emissions associated with the entire digital market, particularly considering its expected increasing adoption.

The extant literature has started to explore digital assets under environmental and social perspectives (see Wendl et al. [31] for a review). Goodkind et al. [28] show that, both in the U.S. and in China, the rising energy costs to mine one Bitcoin might result in a precipitous decline in the overall social benefits. Truby et al. [5] indicate that Bitcoin's annual emissions in 2021 were estimated to be responsible for around 19,000 future deaths. According to Howson and de Vries [32], with the growth in cryptocurrency adoption, increased climate change is expected and is predicted to be the most impactful on poor and vulnerable communities. Zhang et al. [7] note that the energy usage of Bitcoin Granger causes carbon emissions, and that this effect is concentrated in the right tail quantiles. Thus, the significance of decarbonization of digital assets in the context of solving environmental problems cannot be toiled with. Initial results from the literature set the foundations for our study and suggest that digital markets might be susceptible to the effects of climate risks and policies. In this research we assess the impact of climate-related risks on cryptocurrencies, NFTs, and DeFi markets.

The existing literature on digital assets and climate risks primarily focuses on the environmental impact of cryptocurrencies, particularly the related energy consumption and associated greenhouse gas emissions [5,28]. Indeed, many studies have explored how the energy-intensive processes of blockchain networks, especially Bitcoin and Ethereum, contribute to climate change, with some suggesting that these assets may exacerbate global warming if left unchecked [7,32]. However, such studies have largely overlooked the direct relationship between climate-related risks, both physical and transition risks, and the financial risk profiles of digital assets. Additionally, much of the existing research focuses on returns, volatility, and spillover effects [33,34], whereas few studies have examined the returns of these assets in the context of climate change. Another limitation of the existing research is the reliance on linear models, which often fail to capture the asymmetric nature of risk behavior [21].

This study innovatively addresses the identified gaps in the literature by exploring how climate-related risks impact the digital assets return, including cryptocurrencies, NFTs, and DeFi. Unlike previous studies, we extend the literature by employing the QQR approach, which allows us to study the bi-directional relationship between climate risks and digital assets' returns across different quantiles. This methodology fosters a more detailed understanding of how varying levels of climate risks impact digital assets' risk profiles, capturing the heterogeneity in their responses across different market conditions [21]. Ilhan et al. [22] present the pricing mechanism in the options markets concerning climate policy uncertainty in the downside tail risk of carbon-intensive firms, finding that carbon-intensive firms pay more for option insurance against downside tail risks. While there are several studies conducted on conventional financial markets [25,33–40], we are the first to test this hypothesis in carbon-intensive cryptocurrencies, NFTs, and DeFi markets. Thus, our study fills a significant gap in the literature by introducing both a novel risk measurement framework and an advanced statistical method for assessing the intersection of climate change and digital asset markets.

3. Empirical technique

3.1. Quantile-on-quantile regression (QQR)

We employ Sim and Zhou [21]'s QQR technique to explore any asymmetric impact of climate-related risks on the cryptocurrencies, NFTs, and DeFi assets return. Unlike a standard QR approach, which analyzes the impact of variables in a one-way direction, QQR allows for the assessment of a bi-directional relationship, thereby capturing how different quantiles of climate-related risks influence

[2] Metric tons of carbon dioxide equivalent.

[3] Source: Cambridge Bitcoin Electricity Consumption Index (CBECI) (ccaf.io).

[4] The Bitcoin market capitalization equals 51.7 % as coinmarketcap.com accessed on 08/11/2023.

various quantiles of the return series. This is particularly useful for understanding the heterogeneous effects that varying levels of climate risks (from low to high) may have on the digital assets return. Furthermore, by integrating non-parametric estimations, QQR enables a deeper exploration of the conditional distributions between the independent and dependent variables, offering valuable insights into the complex dynamics that exist between climate risks and digital asset risk profiles [21]. This methodology is well suited for our analysis due to allowing us to assess how different climate risk states impact digital assets across various quantiles of the return, highlighting the potential asymmetries in these relationships. QQR represents therefore a suitable methodology for the current analysis as it allows us to explore how different climate risk states (from low to high quantiles) in turn impact various quantiles of the cryptocurrencies, NFTs, and DeFi assets return, while acknowledging that high or low climate risks might have heterogeneous effects on various quantiles of assets' return [41].

Let the non-parametric function of the QQR model run as follows:

$$\mathrm{R}_t = \beta^{\theta} CRR_{t-1} + \alpha^{\theta}\mathrm{R}_{t-1} + \varepsilon_t^{\theta} \tag{1}$$

where R_t denotes return of cryptocurrencies, NFTs, or DeFi assets, and CRR_t represents climate-related risk, either physical or transition, at time t. θ denotes the returns of each cryptocurrency, NFT, and DeFi asset at θ_{th} quantile, and $\beta^{\theta}(.)$ is unknown. CRR^{τ} is measured as the first-order Taylor approximation utilizing the specifications listed as:

$$\beta^{\theta} CRR_{t-1} \approx \beta^{\theta} CRR^{\tau} + \beta^{\theta}(CRR^{\tau})(CRR_{t-1} - CRR^{\tau}) \equiv b_0(\theta,\tau) + b_1^{'}(\theta,\tau) \times (CRR_{t-1} - CRRt^{\tau}) \tag{2}$$

where τ represents the τ_{th} quantile of climate-related risks. By substituting the first-order Taylor approximation of Eq. (2) to Eq. (1) we get:

$$\mathrm{R}_t = \beta^{\theta}(CRR^{\tau}) + \beta^{\theta}(CRR^{\tau})(CRR_{t-1} - CRR^{\tau}) + \alpha^{\theta}\mathrm{R}_{t-1} + \varepsilon_t^{\theta} \tag{3}$$

Eq. 3 is explained by the following:

$$\min_{b_0(\theta,\tau),\ b_1(\theta,\tau),\ \alpha^{\theta}(\tau)} \sum_{t=1}^{T} \rho_{\theta}\left[\mathrm{R}_t - b_0 - b_1(CRR_{t-1} - CRR^{\tau}) - \alpha^{\theta}\mathrm{R}_{t-1}\right] K\left(\frac{CRR(CRR_{t-1}) - \tau}{h}\right) \tag{4}$$

where $\rho_{\theta}(.)$ solving for θth of r_t represents the absolute value of the slope function, and the Gaussian kernel function $K(.)$ with h is the bandwidth selected by the cross-validation technique.

3.2. Quantile coherency method

For additional robustness we employ a quantile cross-spectral dependency approach introduced by Baruník and Kley [57] to examine the dependence structure between climate risk and digital assets. Consequently, building upon the foundational research of Baruník and Kley [57] and additional studies (e.g., [20,58]), we determine two accurate stationary procedures for factors $(R_t)_{t\epsilon\mathbb{Z}}$, characterized by mechanisms $R_t = (R_{t,x}, R_{t,y})$, where x and y respectively denote proxies for a pair of variables. Consequently, the quantile coherency between these two methods $(R^{x,y})$ is articulated as follows:

$$\mathscr{R}^{x,y}(\omega;\tau_1,\tau_2) := \frac{f^{x,y}(\omega;\tau_1,\tau_2)}{\left(f^{x,x}(\omega;\tau_1,\tau_1)f^{y,y}(\omega;\tau_2,\tau_2)\right)^{1/2}} \tag{5}$$

where $-\pi < \omega < \pi$ denotes the quantile cross-spectral density, and $(\tau_1,\tau_2)\in[0,1]$. $f^{x,y}$, $f^{x,x}$, and $f^{y,y}$ are the quantile spectral densities of the processes $R_{t,x}$ and $R_{t,y}$, which can be derived from the Fourier transform of a matrix of quantile cross-covariance kernels $\Gamma(\tau_1,\tau_2)$ defined as $(f(w;\tau_1,\tau_2))_{x,y}$.We thus have:

$$\Upsilon_k^{x,y} := Cov\left(I\left\{J_{t+k,x} \le q_{x(\tau_1)}\right\}, I\left\{J_{t+k,y} \le q_{y(\tau_2)}\right\}\right) \tag{6}$$

For $y\in\{1,\ldots,d\}$, $\tau_1,\tau_2\in[0,1]$, and event A is represented by the function I{A}. Diversifying k and selecting $x \neq y$ provide a crucial indicator of serial correlation and cross-sectional dependence, respectively. The frequency domain produces the matrix of quantile cross-spectral density kernels defined as $f(w;\tau_1,\tau_2) := (f(w;\tau_1,\tau_2))_{x,y}$, where:

$$f^{x,y}(w;\tau_1,\tau_2) := (2\pi)^{-1}\sum_{k=-\infty}^{\infty}\Upsilon_k^{x,y}(\tau_1,\tau_2)e^{-ik\omega} \tag{7}$$

Utilizing smoothed quantile cross-periodograms, we measure quantile coherency as outlined by Baruník and Kley [57]:

$$\widehat{G}_{n,R}^{x,y}(w;\tau_1,\tau_2) := \frac{2\pi}{n}\sum_{s=1}^{n-1} W_n\left(\omega - \frac{2\pi s}{n}\right) I_{n,R}^{x,y}\left(\frac{2\pi s}{n},\tau_1,\tau_2\right) \tag{8}$$

Here, W_n and $I_{n,R}^{x,y}$ denote the order of weight functions and the rank-based copula cross-periodograms matrix, correspondingly. The quantile coherency estimation is expressed:

$$\widehat{\mathscr{R}}^{x,y}_{n,R}(w;\tau_1,\tau_2) := \frac{\widehat{G}^{x,y}_{n,R}(w;\tau_1,\tau_2)}{\left(\widehat{G}^{x,x}_{n,R}(w;\tau_1,\tau_1)\widehat{G}^{y,y}_{n,R}(w;\tau_2,\tau_2)\right)^{1/2}} \tag{9}$$

This study examines the coherency matrices by analyzing three quantiles, lower (0.05), medium (0.5), and upper (0.95), in conjunction with three quantile levels - specifically, left (0.05|0.05), middle (0.5|0.5), and right (0.95|0.95) tails of the joint distribution. We further categorize the coherency into three temporal horizons: high value (quarterly), medium value (semi-annually), and low value (annually), corresponding to $\omega \in 2\pi\{1/3,1/6,1/12\}$. This analysis utilizes the quantspec package from R Statistical Software.

In Eq. (7) the cross-spectral density of kernels $f^{x,y}(w;\tau_1,\tau_2)$ can be decomposed into real and imaginary components (Baruník and Kley, 2019). The real component represents the co-spectrum of the processes $\left(I\{R_{t,x} \leq q_x(\tau_1)\}\right)_{t\epsilon\mathbb{Z}}$ and $\left(I\left\{R_{t,y} \leq q_y(\tau_2)\right\}\right)_{t\epsilon\mathbb{Z}}$, while the imaginary component delineates the quadrature spectrum, mitigating various sources of noise coherence. Nonetheless, for the sake of clarity and improved presentation, we solely present the actual components of our quantile coherency estimations. The imaginary components of all quantile coherencies are estimated, but the plots are not presented here for the sake of brevity; still, all findings are accessible upon reasonable request.

4. Data

Our climate-related risks data are obtained from Bua et al. [42]. Specifically, we consider the daily Physical Risk Index (PRI) and the Transition Risk Index (TRI) as proxies for physical and transition climate risks, respectively. A growing number of studies rely on PRI and TRI (see, among others, [15,24,25,43–45]). Starting from a list of scientific and authoritative texts on climate change, Bua et al. [42] first separate the texts into a physical and a transition risk document, from which they build two distinct vocabularies. The authors then compare the vocabularies terms, and their relative usage intensity (term-frequency inverse document frequency scores), with a large corpus of news articles sourced from Reuters News using the cosine-similarity techniques, also adopted by Engle et al. [34]. Thus, they produce two "concern" time series reflecting the level of media discussion on physical and transition risks issues.

PRI and TRI are finally obtained as residuals, or innovation, from the "concern" time series modelled as an AR (1). Unlike other climate risk indicators, PRI and TRI express the complex traits of physical and transition risks induced by climate change. On one side, PRI is able to detect risks stemming from both chronic (e.g., sea level rise) and acute (e.g., floods) physical climate disasters, along with adaptation measure news. On the other side, TRI identifies risks associated with the shift to a low-carbon, greener economy, usually prompted by climate or environmental policy changes, advancements in technology, and/or changes in public preference. PRI and TRI values are normalized to a 0–100 scale.

For what concerns the data for digital assets, we consider a variety of blockchain-based assets that are widely used in the extant literature on cryptocurrencies, NFTs, and DeFi and that represent a substantial portion of each market and earliest launch date [10,11,13]. The selection of assets is guided by our goal of covering a wide spectrum of blockchain-based assets with varying characteristics and use cases, ensuring that our analysis captures the dynamics of the broader digital asset ecosystem. In addition, we focus on assets with an early launch date to ensure they have a sufficient historical data series, which is crucial for a robust empirical analysis, particularly when examining the impact of climate-related risks over time. Specifically, our sample comprises four cryptocurrencies (Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Ripple (XRP)), four NFTs (Syscoin (SYS), DigiByte (DGB), Enjin Coin (ENJ), and Decentraland (MANA)), and four DeFi assets (Maker (MKR), Chainlink (LINK), Basic Attention Token (BAT), and Bancor (BNT)), for which we collect daily closing prices denominated in USD from coinmarketcap. Our sample period goes from October 20, 2017 to June 30, 2022, where the starting date is based on data availability of all the digital assets jointly, and ending date is based on the availability of PRI and TRI. Our sample period includes recent major international climate events such as the 2019 UN Climate Action Summit and the 2021 UN Climate Change Conference (COP26) along with the relative introduction of climate mitigation policies, and

Table 1
Selected assets and variable list.

Variable Class	Variable	Description	Data Source
Climate Risk	TRI	Transition Risk Index	Bua et al. (2024)
	PRI	Physical Risk Index	
Cryptocurrency	BTC	Bitcoin	coinmarketcap.com
	ETH	Ethereum	
	LTC	Litecoin	
	XRP	Ripple	
NFT	SYS	Syscoin	coinmarketcap.com
	DGB	DigiByte	
	ENJ	Enjin Coin	
	MANA	Decentraland	
DeFi	MKR	Maker	coinmarketcap.com
	LINK	Chainlink	
	BAT	Basic Attention Token	
	BNT	Bancor	

Notes: This table reports the acronyms for each variable used in this study, along with the variable's description/full name, class (between cryptocurrency, NTF, DeFi, and climate risk), and data source.

other events including COVID-19 and the Russia-Ukraine war. Table 1 summarizes the main data used in the current study along with the data source for each digital asset and for the climate risk indicators.

We then compute the daily digital assets' returns and changes in climate risk as $r_{i,t} = \log(P_{i,t}) - \log(P_{i,t-1})$. Fig. 1 illustrates the variable series for changes in cryptocurrencies, NFTs, DeFi prices, and climate-related risks. The figure shows some similar peak points in returns of cryptocurrencies, NFTs, and DeFi particularly during COVID-19.

Table 2 displays concise statistical information of the variables. The digital asset with the largest average return risk is MKR (0.004), whereas ETH has the smallest amount of return (-0.001) among the sampled assets. The variance of SYS return (0.010) is comparatively higher than the other selected assets, indicating higher variation in the return of SYS. For what concerns the climate risk indicators, transition risk exhibits a higher average value (0.001) with respect to physical risk (0.001), whereas both TRI and PRI variances are quite high (0.252 and 0.546, respectively), implying uncertainty towards climate-related risk. BTC, LTC, ENJ, and LINK are characterized by negative skewed returns, whereas they rest as connoted by positive skewness. Finally, the kurtosis values show that all variables follow a fat tailed distribution. The ERS unit-root test verifies that all variables are stationary.

5. Empirical results

5.1. QQR results of transition climate risks

We first examine how climate transition risk (TRI) affects the returns of cryptocurrencies, NFTs, and DeFi, with the results displayed in Fig. 2. The figure shows the slope coefficients $\beta_1(\theta,\tau)$, in turn representing the impact of the τ_{th} quantile of TRI on the θ_{th} return quantile of cryptocurrencies (a), NFTs (b), and DeFi (c). Due to the non-parametric approach employed in QQR estimates, it is not practical to evaluate the significance levels of the coefficients (see [21,47]). TRI is found to have a heterogeneous effect on cryptocurrencies, NFTs, and DeFi returns across its quantiles.

Fig. 2(a) illustrates the QQR results for the relationship between TRI and cryptocurrencies. When both TRI and cryptocurrencies are in the lowest quantile studied ($\tau = 0.05$), there is a positive effect of TRI on cryptocurrencies, indicating that low TRI increases cryptocurrencies' return. In the case of BTC, for instance, when TRI is in a lower quantile, there is a positive effect, whereas when TRI is in its mid-quantile ($\tau = 0.50$), there is a heterogeneous effect across the quantiles of BTC. Lastly, when TRI is in an upper quantile ($\tau = 0.95$) we document a negative impact of transition climate risk across the quantiles of BTC, meaning that an unexpected discussion around the process of transition towards a greener economy decreases the cryptocurrency's return. Similar results are documented for ETH, LTC, and XRP, and thus our results show asymmetry across the extreme quantiles (τ =0.05 and 0.95).

These findings imply that lower (higher) climate transition risk increases (decrease) cryptocurrencies' return. This result is attributed to the energy consumption of cryptocurrencies for mining, with the majority of this energy coming from fossil fuels that contribute to climate change. As TRI increases, the carbon footprint of cryptocurrency mining may become a liability, leading to regulatory actions that could reduce cryptocurrency values. This sharp drop can lead to a significant fall in the returns of cryptocurrencies. Furthermore, as climate change becomes a growing concern among investors, investor sentiment is shifting toward low-

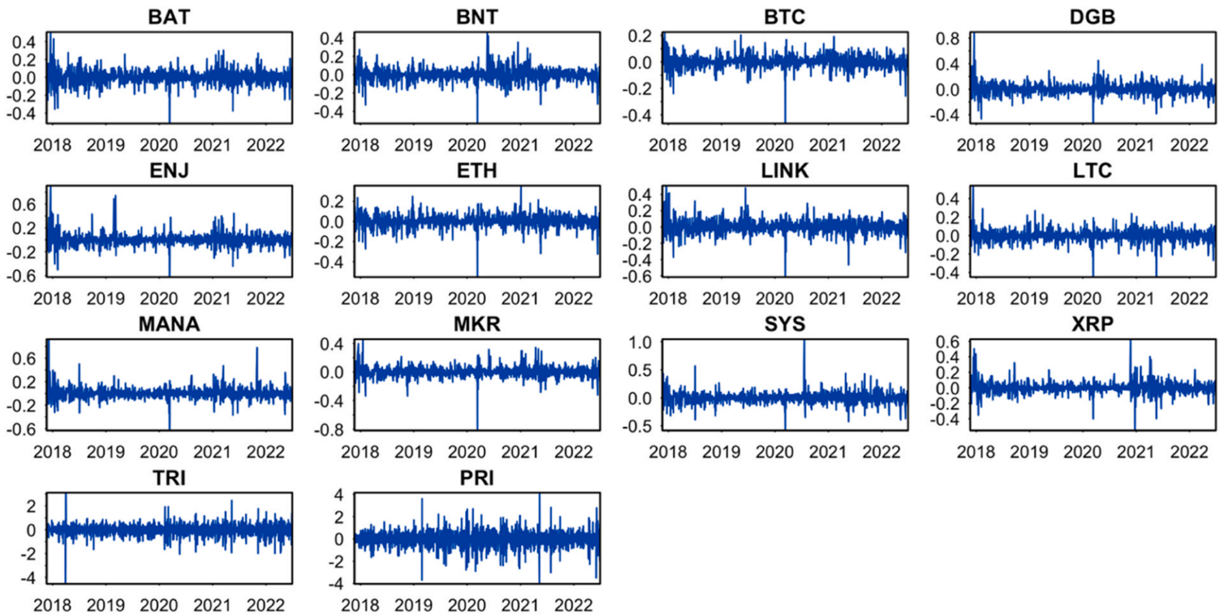

Fig. 1. Series of cryptocurrencies, NFTs, and DeFi returns, and changes in climate risk. Notes: This figure shows the daily time series evolution for the returns of cryptocurrencies (BTC, ETH, LTC, and XRP), NFTs (SYS, ENJ, MANA, and DGB), and DeFi assets (MKR, LINK, BAT, and BNT), along with the dynamics of climate-related risks' transition and physical time series (TRI and PRI, respectively).

Table 2
Results of summary statistics.

	Mean	Variance	Skewness	Kurtosis	JB	ERS	Q(20)	Q2(20)
BTC	0.001	0.006	−0.006	5.325 ***	1414.481 ***	−12.850 ***	16.671 *	74.871 ***
ETH	−0.001	0.005	0.123 *	6.736 ***	2266.135 ***	−12.372 ***	32.868 ***	69.318 ***
LTC	0.001	0.002	−0.852 ***	9.801 ***	4935.513 ***	−11.960 ***	35.019 ***	26.102 ***
XRP	0.000	0.008	0.891 ***	12.982 ***	8563.723 ***	−11.139 ***	26.099 ***	60.448 ***
SYS	0.003	0.010	1.256 ***	14.069 ***	10187.403 ***	−8.346 ***	18.192 **	72.010 ***
ENJ	0.001	0.004	−0.753 ***	8.181 ***	3450.980 ***	−12.440 ***	18.961 **	28.660 ***
MANA	0.003	0.007	0.076	6.451 ***	2076.789 ***	−9.375 ***	15.971 *	83.984 ***
DGB	0.000	0.004	0.093	9.670 ***	4665.794 ***	−10.891 ***	72.404 ***	94.762 ***
MKR	0.004	0.009	1.327 ***	14.748 ***	11198.959 ***	−14.779 ***	50.314 ***	64.043 ***
LINK	0.001	0.006	−0.514 ***	15.136 ***	11478.663 ***	−12.019 ***	20.342 **	36.506 ***
BAT	0.000	0.009	1.010 ***	15.145 ***	11644.016 ***	−11.762 ***	22.715 ***	21.225 ***
BNT	0.000	0.006	0.799 ***	12.861 ***	8377.169 ***	−11.298 ***	23.072 ***	107.471 ***
TRI	0.001	0.252	−0.710 ***	8.528 ***	3728.073 ***	−5.836 ***	377.751 ***	199.031 ***
PRI	0.001	0.546	−0.298 ***	4.126 ***	866.809 ***	−6.233 ***	422.127 ***	238.637 ***

Notes: This table reports the summary statistics including variables' mean, variance, skewness (D′Agostino [53], kurtosis (Anscombe and Glynn [54], Jarque and Bera normality test – JB (Jarque and Bera [55], and the ERS uni-root test (Elliott et al. [56]. $*p < 0.1$,$**p < 0.05$,$***p < 0.01$.

carbon industries, which may reduce demand for cryptocurrencies associated with carbon-intensive mining processes. On the other hand, when TRI is low there is less awareness about climate transition, which leads to an increase in their returns. These findings align with the perspective that cryptocurrencies' performances and climate change risks are negatively related [2,7,30], further showing that this nexus is explained by the risk transmission from climate risks to cryptocurrencies.

Fig. 2(b) depicts the QQR findings of the relationship between TRI and NFTs. The results show that when both TRI and NFTs are in a lower quantile (τ =0.05), TRI has a positive effect on NFTs, indicating that lower TRI increases the returns of NFTs. This outcome is consistent with the findings for cryptocurrencies. In the case of MANA, for example, when TRI is in a lower quantile ($\tau = 0.05$), there is a positive effect, whereas when TRI is in a mid-quantile (τ =0.50), there is a heterogeneous effect across quantiles of MANA. However, when TRI is in an upper quantile (τ= 0.95), there is a negative impact across all quantiles of MANA. The outcomes for the other NFTs also exhibit similar results. Thus, the findings present asymmetry across the extreme quantiles (τ =0.05 and 0.95), and a higher (lower) level of TRI decreases (increases) NFTs' return. This can be explained by the carbon footprint of NFTs, which are created and stored on blockchain networks and which consume a lot of energy to run due to the computational power required for mining, verifying, and validating transactions on the network. Thus, climate transition risk decreases the returns of NFTs by reducing market demand and causing their value to fall. For example, as investors are becoming more aware of the dangers involved with climate change, they may be less inclined to invest in carbon-intensive industries, reducing demand for NFTs associated with these industries. This could then bring about a decrease in the value of these NFTs. This outcome is in line with the argument by Truby et al. [5] who document that NFTs increase carbon footprint.

Fig. 2(c) presents the QQR result of the relationship between TRI and DeFi. The result of DeFi also shows a similar asymmetric relation as pointed out above for cryptocurrencies and NFTs. For example, the result of MKR illustrates in an upper quantile (τ= 0.95) that there is a negative association between TRI and MKR, denoting climate transition risk decreases DeFi return. Climate transition risk can decrease the return of DeFi protocols by affecting the value of assets that underpin them. For example, if there is a shift toward renewable energy sources, then the value of fossil fuel-based assets may fall, lowering the collateral value of DeFi protocols backed by these assets. As a result, the likelihood of default and systemic risk within the DeFi ecosystem may increase. This conclusion is consistent with the findings of other studies in the literature (see [5,7,46]) that document a negative consequence of the blockchain market on climate change.

5.2. QQR results of physical climate risks

We next examine the effect of physical climate-related risks on cryptocurrencies, NFTs, and DeFi returns, and the results of QQR appear in Fig. 3(a), (b), and (c), respectively. The results of cryptocurrencies and PRI appear in Fig. 3(a) and show heterogeneity across the quantiles. Specifically, there is evidence of an asymmetric impact of PRI on cryptocurrency return, as there is a negative (positive) association when both are in the upper (lower) quantile. The result is almost identical for all cryptocurrencies. These findings are also similar to the results of TRI. Physical climate risk can lower the return of cryptocurrency by affecting the infrastructure that supports cryptocurrency transactions and the availability of energy for mining. Extreme weather events, for example, can damage or disrupt the infrastructure required for cryptocurrency transactions, causing their value to fall. Changes in weather patterns and natural disasters also impact on the availability and cost of energy used for mining, raising the cost of producing cryptocurrencies and reducing their profitability. Other studies (see [2,7,30]) also document that cryptocurrencies negatively impact climate.

The results of NFTs and DeFi are in Fig. 3(b) and (c), respectively, which also show a similar asymmetric impact. This asymmetric impact of PRI on NFTs and DeFi can be explained in the following ways. 1) In the case of NFTs, physical climate risk decreases the returns of NFTs by affecting the demand for and value of NFTs associated with climate-risky physical assets. For example, if a physical asset, such as a piece of artwork, is damaged or destroyed due to a climate-related event, then the value of any associated NFT may fall

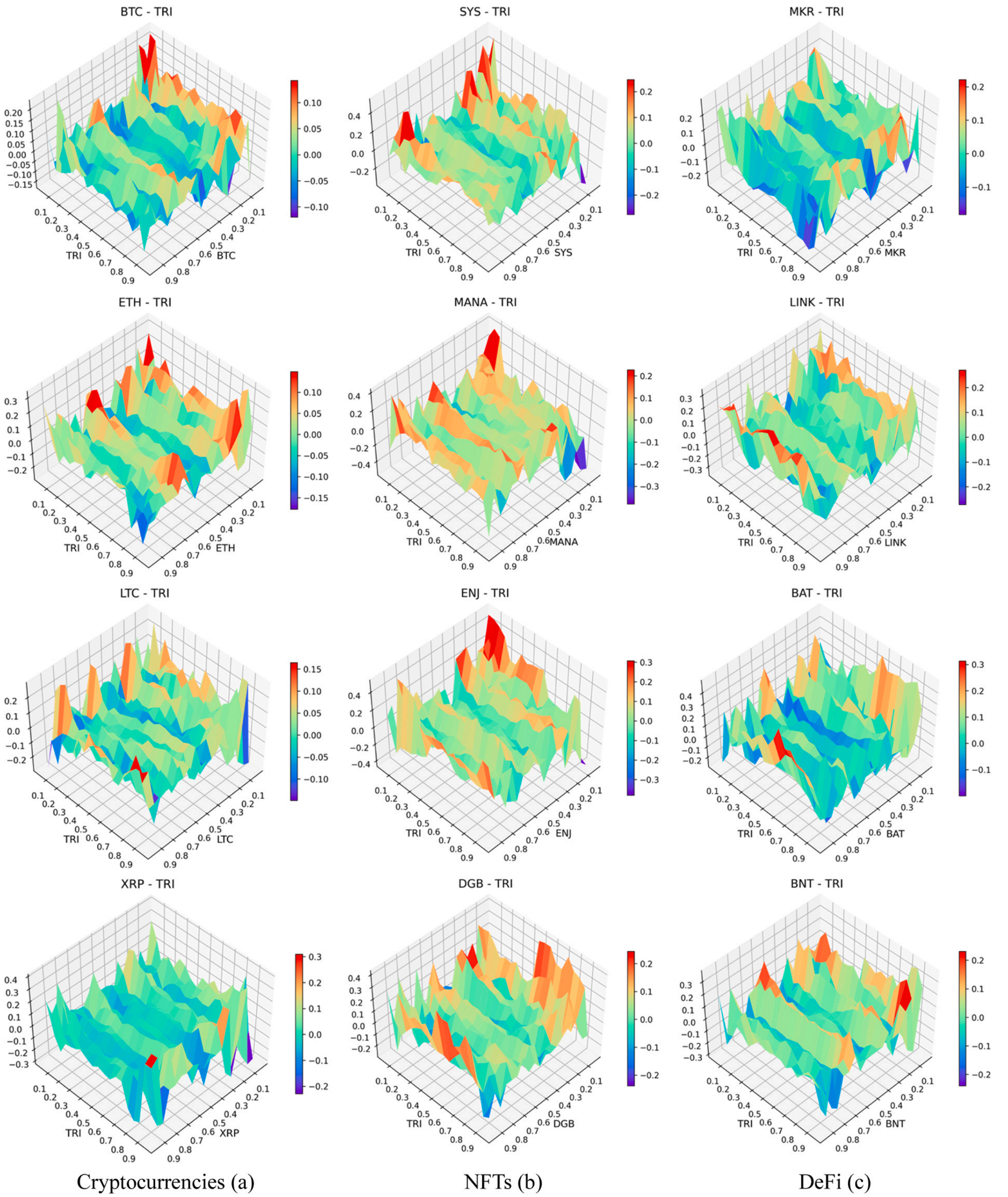

Fig. 2. QQR results of TRI and digital assets. Notes: This figure shows the results from the QQR models for the effects of transition risk (TRI) on the returns of: (a) cryptocurrencies, BTC, ETH, and LTC; (b) NFTs SYS, ENJ, MANA, and DGB; and (c) DeFi assets MKR, LINK, BAT, and BNT.

as the underlying asset's value falls. Furthermore, if demand for NFTs associated with assets exposed to physical climate risk, such as coastal properties, falls, then those NFTs' value may fall as well. 2) Physical climate risk decreases the returns of DeFi protocols by affecting the collateral value of assets that underpin them. For example, if a severe weather event damages the physical infrastructure underlying a collateral asset, then the asset's value may fall, lowering the collateral value of DeFi protocols backed by these assets. As a

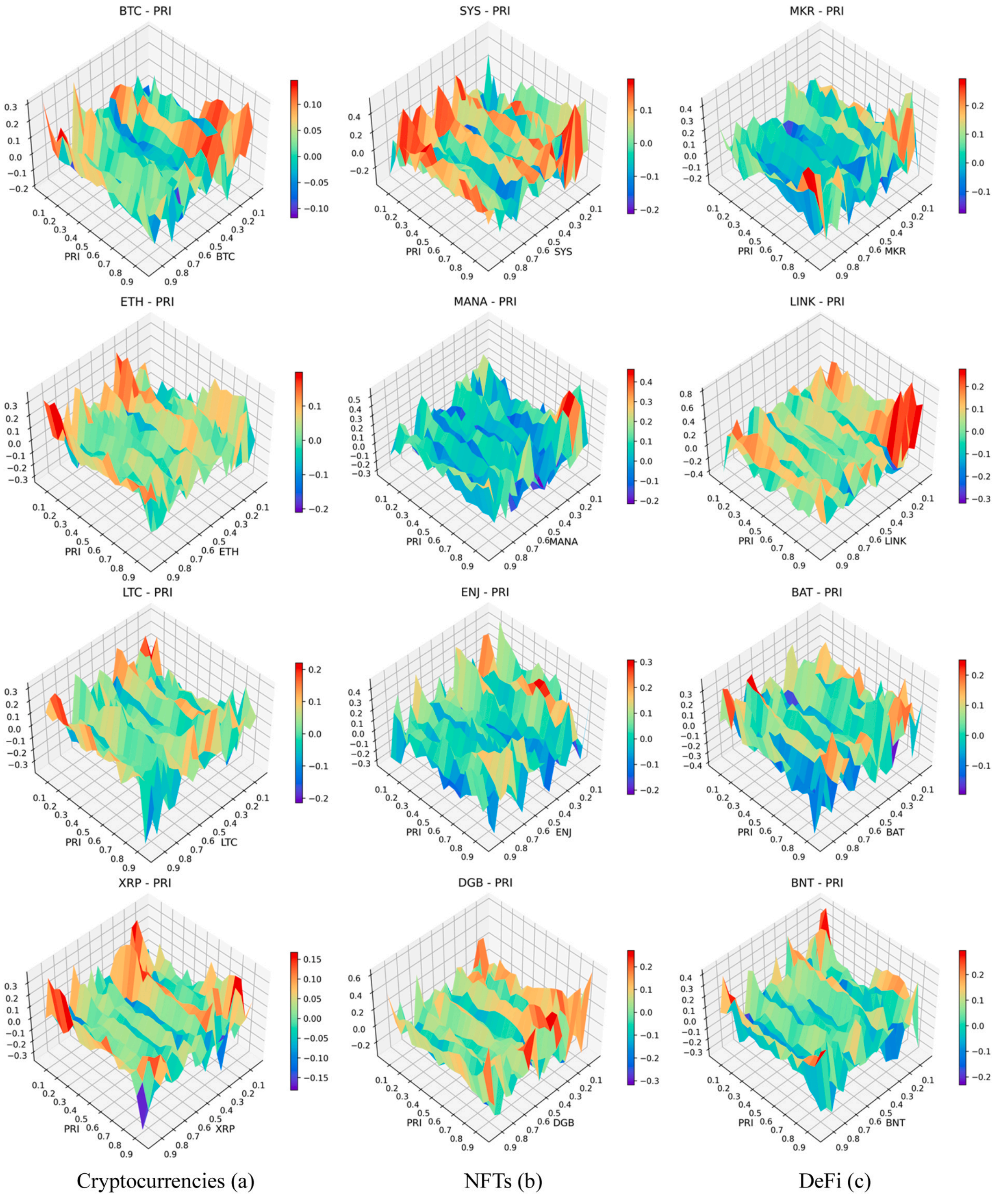

Fig. 3. QQR results of PRI and digital assets. Notes: This figure shows the results from the QQR models for the effects of physical risk (PRI) on the returns of: (a) cryptocurrencies BTC, ETH, and LTC; (b) NFTs SYS, ENJ, MANA, and DGB; and (c) DeFi assets MKR, LINK, BAT, and BNT.

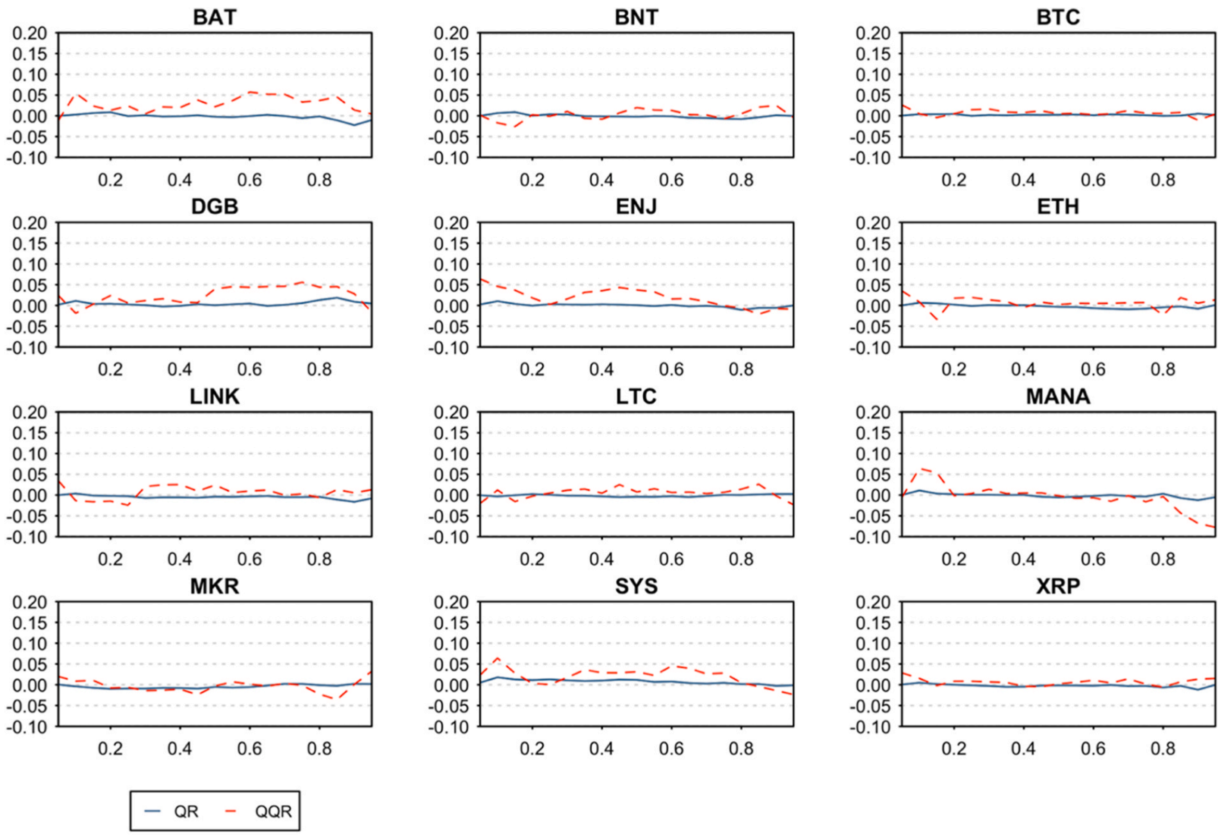

Fig. 4. QQR results from robustness test of TRI.

result, the likelihood of default and systemic risk within the DeFi ecosystem may increase. Our findings are consistent with other studies (see [5,7,46]) that document the blockchain market's negative impact on the environment.

5.3. Robustness test results

As described earlier, QQR is a non-parametric estimation process that does not allow to examine the significance level. However, the QQR estimates can be compared to QR to validate their coefficients, because they are decomposed into specific quantiles of the regressors. Thus, following Ge [47] and Sim and Zhou [21] we examine the robustness of our QQR results by using QR. Specifically, QR is used to validate the QQR findings and to help draw conclusions about the relationships identified by QQR. Figs. 4 and 5 depict this comparison with line graphs displaying the QR and QQR coefficients. These graphs serve two functions. First, they visually depict the trend in cryptocurrencies, NFTs, and DeFi return and the corresponding movements in TRI and PRI. Second, they validate QQR by comparing it to the QR estimates. As a result, these graphs can be used to assess the relationships between variables. The QR and QQR quantiles and estimates are shown on the horizontal and vertical axes, respectively, and the QR and QQR estimates are represented by green and red dotted lines across the quantiles.

Fig. 4 indicates that for all assets there is a negative (positive) impact of TRI on their returns in the upper (lower) quantiles. This result validates our earlier findings and clearly shows asymmetry. Furthermore, the coefficients of QR and average QQR do not highly deviate, indicating robustness of the findings. Fig. 5 also shows similar findings and denotes robustness of the PRI results. Overall, results indicate an asymmetric impact of climate-related risks on the returns of cryptocurrencies, NFTs, and DeFi where higher (lower) climate-related risks decrease (increase) the return. These results are in line with other studies (see [2,3,5,7,30,46,48]) that document the blockchain market's negative consequences on the environment.

5.4. Causality analysis

We examine Granger causality in quantiles for the purpose of further validating the reliability of our findings. Specifically, we employ Troster [49]'s quantile Granger causality test, which allows us to examine bidirectional causality among the returns of

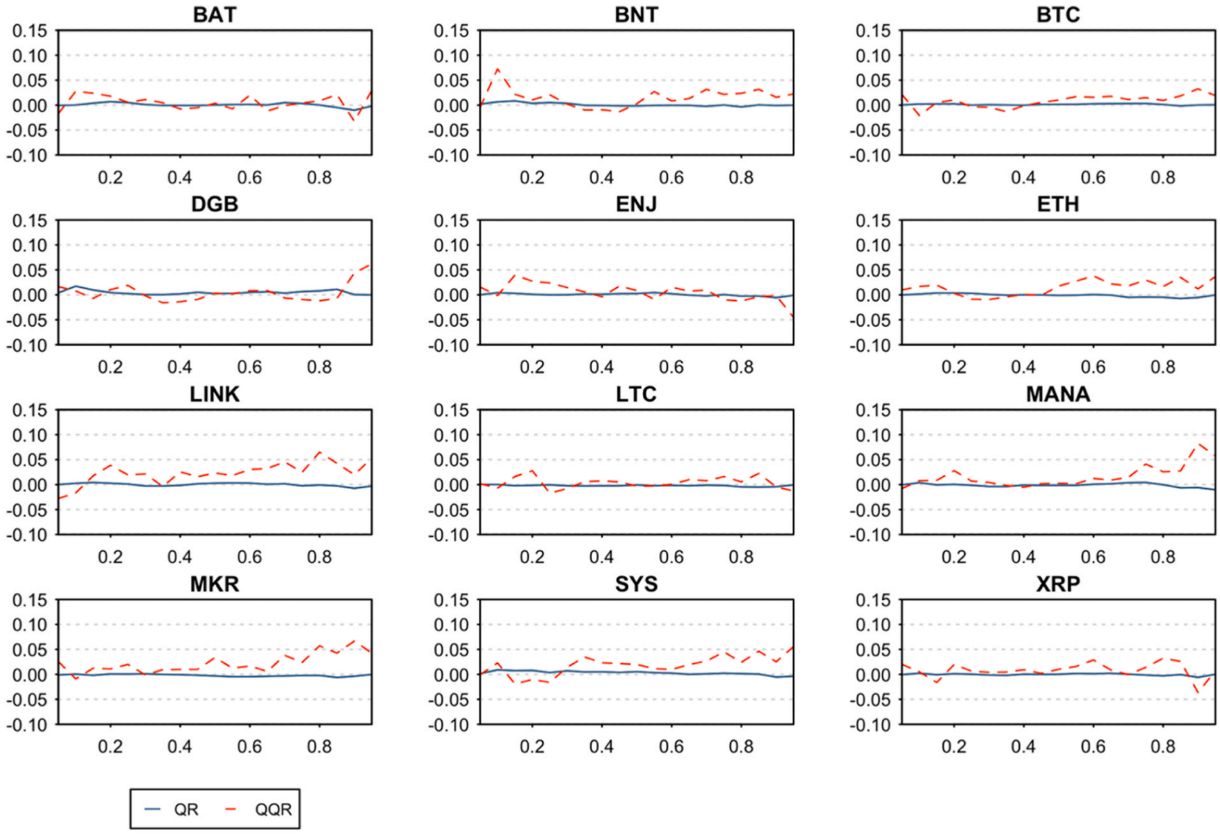

Fig. 5. QQR results from robustness test of PRI.

climate-related risks, cryptocurrencies, NFTs, and DeFi across quantiles [50–52]. The results of the Granger causality test among the returns for TRI, cryptocurrencies, NFTs, and DeFi appear in Table 3. They show that TRI Granger causes the returns of cryptocurrency, NFTs, and DeFi across upper quantiles. However, these three aspects' returns do not Granger cause TRI in most of the quantiles.[5] Thus, there is unidirectional causality from TRI to the returns of cryptocurrencies, NFTs, and DeFi in the upper quantile. The unidirectional result is not surprising as the return does not reflect future climate events, but trading activities do have a significant association with climate risk [30]. The results of the Granger causality test among the returns for PRI, cryptocurrencies, NFTs, and DeFi are in Table 4. The result of PRI also shows a consistent result like that for TRI, indicating unidirectional causality from TRI to the returns of cryptocurrencies, NFTs, and DeFi in the upper quantile. Thus, findings of Granger causality in quantiles further validate our results' robustness and implies climate-related risks impact the returns of cryptocurrencies, NFTs, and DeFi.

5.5. Quantile coherency results

In this section we further examine quantile dependence between climate-related risks and digital asset returns using quantile coherency. Figs. 6 and 7 present the quantile coherence estimates between climate risk and digital assets, based on the quantile cross-spectral method. The plots illustrate the real component of quantile coherence across different return quantiles: lower (0.05|0.05), median (0.50|0.50), and upper (0.95|0.95) quantiles at the 5 % significance level. The horizontal axis represents the monthly frequency cycle, ranging from 0 to 0.5, while the vertical axis indicates the degree of interdependence between the two series. Additionally, the labels on the top horizontal axis associate the quantile relationships with annual (Y), semi-annual (H), and quarterly (Q) frequencies.

The Fig. 6(a) illustrates the quantile coherence between TRI and cryptocurrencies across bearish, normal, and bullish markets. For long-term frequency, coherence between CPU and WTI is generally negative in the lower and upper return quantiles (0.05|0.05 and 0.95|0.95). However, as the frequency shifts from yearly to half-yearly and quarterly, the coherence becomes significantly positive in the upper return quantiles, while it drops notably in the lower quantiles. For the median return quantiles (0.50|0.50), there is an average negative coherence over longer time horizons, which transitions to a positive coherence (between 0.0 and 0.2) as the frequency moves to shorter intervals. These results indicate that significant TRI fluctuations can reduce cryptocurrencies' returns over

[5] Results are omitted for brevity, but are available upon request.

Table 3
Quantile Granger causality test results of TRI to cryptocurrencies, DeFi, and NFTs.

	Cryptocurrencies				NFTs				DeFi			
τ	BTC	ETH	LTC	XRP	SYS	ENJ	MANA	DGB	MKR	LINK	BAT	BNT
0.05	2.03 **	2.02 **	1.92 **	1.92 **	2.12 **	2.09 **	1.94 **	1.8 **	1.92 **	2.53 ***	2.2 **	1.93 **
0.10	0.81	1.05	0.89	0.7	1.03	1.16	0.97	0.91	0.93	1.28	1.05	0.72
0.15	0.61	0.62	0.79	0.79	1.19	0.78	0.73	1.18	0.9	1.27	0.99	0.78
0.20	0.62	0.6	0.63	0.75	0.97	0.64	0.93	0.93	0.87	1.22	1	0.92
0.25	0.64	0.75	0.63	1.02	0.77	0.74	1.13	1.11	1.02	1.31 *	1.33 *	0.74
0.30	0.79	0.9	0.85	1.8 **	0.88	1.18	1.16	1.6 *	1.19	1.49 *	1.39 *	1.03
0.35	0.82	0.82	0.99	2.08 **	1.02	1.06	0.99	1.81 **	1.03	1.33 *	1.39 *	1.1
0.40	1.38 *	1.16	1.08	1.7 **	1.11	1.22	1.04	1.95 **	1.34 *	1.72 **	1.78 **	1.35 *
0.45	1.43 *	1.44 *	1.54 *	1.55 *	1.58 *	1.19	1.23	1.6 *	1.21	1.65 **	1.85 **	1.66 **
0.50	1.61 *	1.27	1.54 *	1.02	1.69 **	1.17	1.15	1.11	1.39 *	1.51 *	1.47 *	1.61 *
0.55	1.6 *	1.42 *	1.37 *	1.47 *	1.8 **	1.44 *	1.34 *	1.39 *	1.61 *	1.5 *	1.9 **	1.47 *
0.60	2.68 ***	2.68 ***	2.84 ***	2.71 ***	3.03 ***	2.81 ***	2.42 ***	2.22 **	2.97 ***	2.52 ***	3.27 ***	2.47 ***
0.65	1.3 *	1.46 *	1.48 *	1.84 **	1.92 **	1.64 *	1.54 *	0.83	1.82 **	1.24	1.48 *	1.12
0.70	1.3 *	1.4 *	1.47 *	1.54 *	1.88 **	1.22	1.56 *	1	1.42 *	1.22	1.37 *	1.02
0.75	1.16	1.34 *	1.28	1.43 *	1.64 *	1.17	1.6 *	1.14	1.52 *	1.5 *	1.43 *	1.07
0.80	1.44 *	1.34 *	1.34 *	1.41 *	1.78 **	1.41 *	1.73 **	1.34 *	1.67 **	1.8 **	1.48 *	1.21
0.85	1.79 **	1.64 *	1.97 **	1.74 **	2.12 **	1.87 **	2.12 **	1.66 **	1.72 **	2.24 **	1.83 **	1.65 **
0.90	2.24 **	1.95 **	2.62 ***	2.27 **	2.28 **	2.05 **	2.28 **	2.02 **	2.14 **	2.83 ***	2.26 **	2.09 **
0.95	5.00 ***	3.45 ***	1.81 **	3.44 ***	5.96 ***	3.96 ***	0.77	5.56 ***	6.45 ***	6.53 ***	5.49 ***	3.40 ***

Notes: This table reports the results from the quantile Granger causality test of the impact of transition climate risk (TRI) to the returns of cryptocurrencies, NFTs, and DeFi assets, for different quantile levels τ. $^{*}p < 0.1$,* $^{*}p < 0.05$,$^{***}p < 0.01$.

Table 4
Quantile Granger causality test results of PRI to cryptocurrencies, DeFi, and NFTs.

	Cryptocurrencies				NFTs				DeFi			
τ	BTC	ETH	LTC	XRP	SYS	ENJ	MANA	DGB	MKR	LINK	BAT	BNT
0.05	3.21 ***	2.72 ***	3.25 ***	3.21 ***	3.14 ***	3.54 ***	3.64 ***	3.16 ***	2.98 ***	2.94 ***	2.91 ***	3.27 ***
0.10	1.45 *	1.27	1.92 **	1.31 *	1.52 *	1.65 **	2.12 **	1.84 **	1.46 *	1.38 *	1.33 *	1.75 **
0.15	1.32 *	0.97	1.39 *	1.24	1.23	1.44 *	1.79 **	1.53 *	1.45 *	1.59 *	1.18	1.39 *
0.20	1.17	1.01	1.49 *	1.16	1.06	1.64 *	2.04 **	1.36 *	1.13	1.24	1.08	1.03
0.25	0.94	1.2	1.23	1.31 *	1.15	1.42 *	1.76 **	1.34 *	1.41 *	1.51 *	1.17	1.31 *
0.30	1.1	1.75 **	1.56 *	1.57 *	1.41 *	1.78 **	2.09 **	1.3 *	1.86 **	2.35 ***	1.42 *	1.35 *
0.35	1.25	1.96 **	1.77 **	1.84 **	1.58 *	1.82 **	2.5 ***	1.31 *	1.43 *	2.38 ***	1.68 **	1.46 *
0.40	1.34 *	2 **	2.01 **	1.94 **	1.59 *	1.72 **	2.67 ***	1.6 *	1.47 *	2.26 **	2.08 **	1.45 *
0.45	1.06	1.6 *	1.65 **	1.46 *	1.74 **	1.6 *	2.17 **	1.7 **	1.29 *	2.18 **	1.94 **	1.38 *
0.50	1.4 *	1.47 *	1.6 *	1.89 **	1.6 *	2.12 **	2.32 **	1.91 **	1.67 **	2.38 ***	1.93 **	1.35 *
0.55	1.4 *	1.4 *	1.68 **	1.83 **	1.69 **	1.87 **	2.41 ***	1.76 **	1.62 *	2.39 ***	1.89 **	1.3 *
0.60	3.3 ***	3.25 ***	3.28 ***	3.6 ***	3.13 ***	3.58 ***	4.44 ***	3.36 ***	3.2 ***	3.7 ***	3.46 ***	3.09 ***
0.65	1.49 *	1.44 *	1.71 **	1.95 **	1.73 **	2.24 **	2.5 ***	1.53 *	2.15 **	2.16 **	1.58 *	1.26
0.70	2.76 ***	2.35 ***	2.79 ***	2.59 ***	2.49 ***	3.73 ***	3.35 ***	2.97 ***	2.41 ***	3.03 ***	2.59 ***	2.26 **
0.75	2.2 **	2.31 **	2.61 ***	2.11 **	2.27 **	3.09 ***	2.73 ***	2.57 ***	2.17 **	2.53 ***	2.08 **	1.99 **
0.80	1.89 **	2.29 **	2.5 ***	1.94 **	1.83 **	2.24 **	2.47 ***	2.29 **	2.19 **	2.07 **	1.85 **	2.13 **
0.85	1.61 *	1.5 *	1.69 **	1.35 *	1.18	1.2	1.51 *	1.61 *	1.72 **	1.11	1.52 *	1.53 *
0.90	2.34 ***	2.87 ***	1.35 *	3.97 ***	5.61 ***	4.41 ***	1.49 *	5.11 ***	6.08 ***	6.36 ***	3.57 ***	5.86 ***
0.95	3.26 ***	1.53 *	1.49 *	5.18 ***	6.51 ***	2.10 **	1.81 **	6.38 ***	5.95 ***	7.10 ***	4.75 ***	6.56 ***

Notes: This table reports the results from the quantile Granger causality test for the impact of physical climate risk (PRI) to the returns of cryptocurrencies, NFTs, and DeFi assets, for different quantile levels τ. $^{*}p < 0.1$,* $^{*}p < 0.05$,$^{***}p < 0.01$.

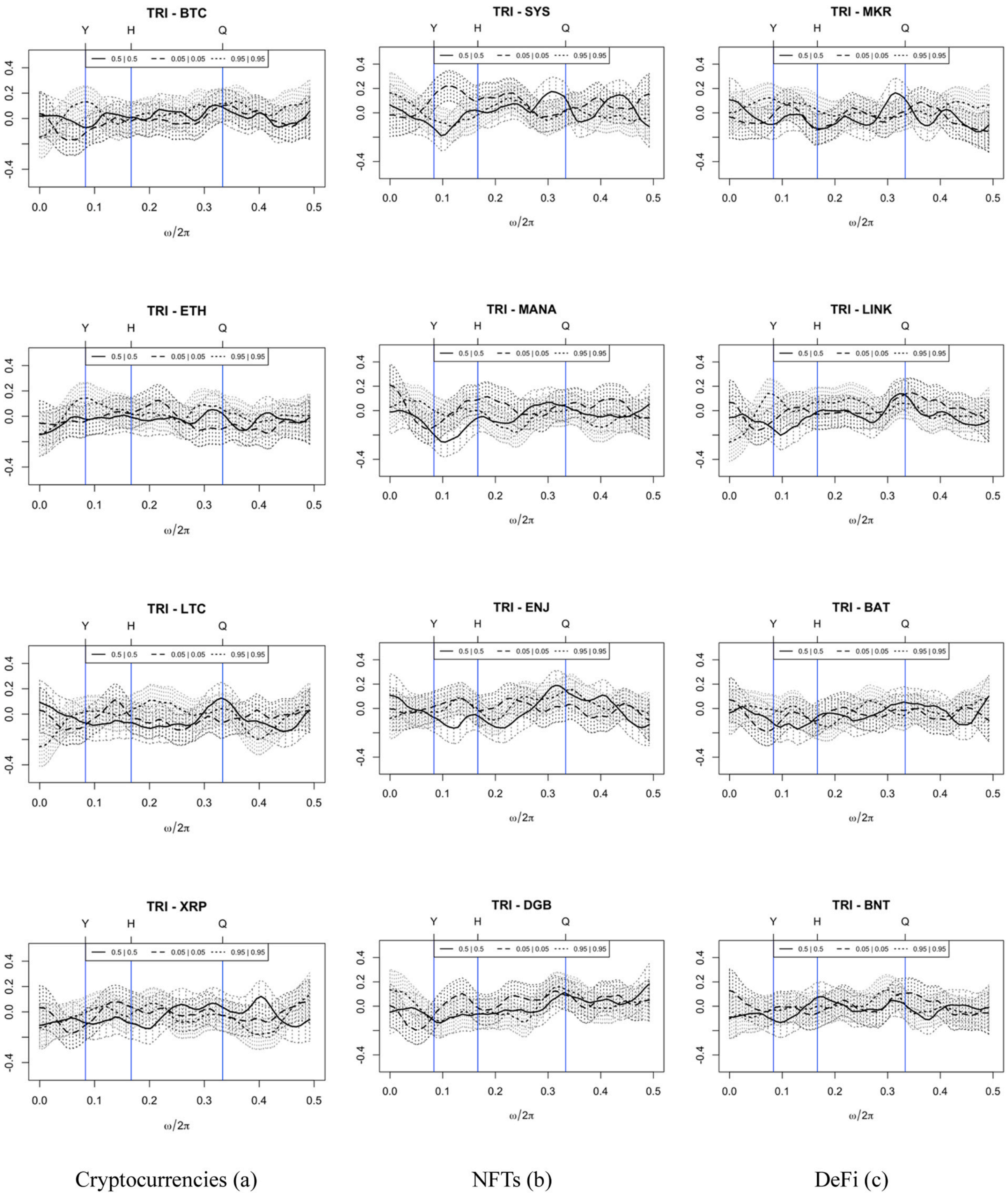

Fig. 6. Quantile coherency results of TRI and digital assets. Notes: This figure shows the results from the Quantile coherency for the effects of transitional risk (TRI) on the returns of: (a) cryptocurrencies BTC, ETH, and LTC; (b) NFTs SYS, ENJ, MANA, and DGB; and (c) DeFi assets MKR, LINK, BAT, and BNT.

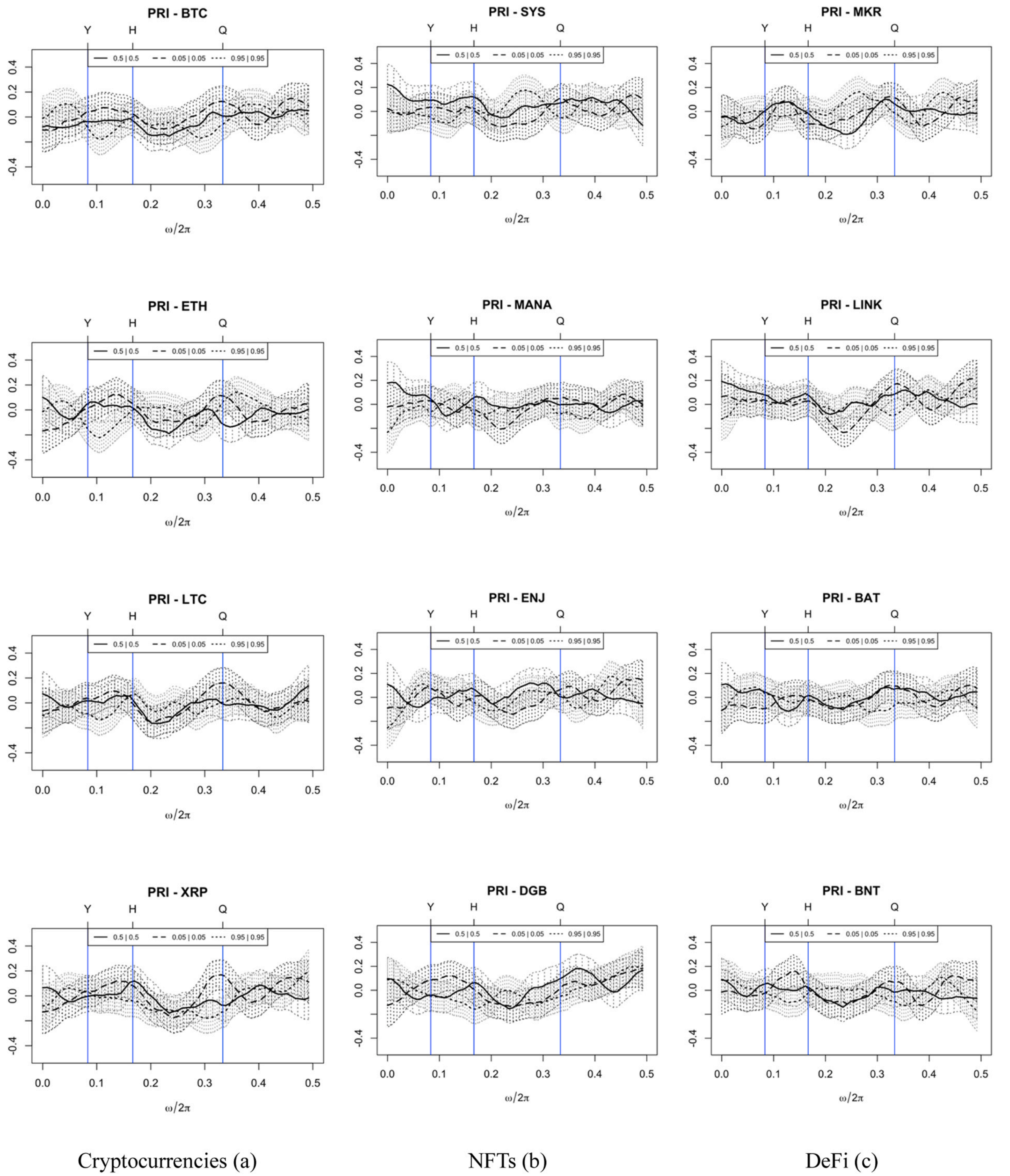

Fig. 7. Quantile coherency results of PRI and digital assets. Notes: This figure shows the results from the Quantile coherency for the effects of physical risk (PRI) on the returns of: (a) cryptocurrencies BTC, ETH, and LTC; (b) NFTs SYS, ENJ, MANA, and DGB; and (c) DeFi assets MKR, LINK, BAT, and BNT.

both the long term and short term. Similar results are witnessed for NFTs and DeFi assets.

Fig. 7(a) highlights the quantile dependence between PRI and cryptocurrencies. Across most frequencies, except for the medium range, there is a significantly negative relationship in the normal return quantile, suggesting strong hedging potential. At medium frequencies, the higher quantile shows a negative correlation, which shifts further negative at lower frequencies. A lower quantile generally exhibits a positive relationship across all frequencies. The observed positive correlation between PRI and cryptocurrencies across various quantiles and frequencies may be influenced by the interplay between environmental policies and market expectations. Similar results are documented for the rest of the assets. Overall, this result aligns with earlier findings from QQR and quantile Granger causality, indicating a heterogeneous impact of climate risk on the digital asset market.

6. Conclusion and policy implications

Regulators, policymakers, and investors are increasingly concerned about the nexus between climate-related risks and digital assets given the high carbon footprint and environmental impact of these assets. This paper provides a comprehensive analysis examining how climate risks, both physical and transition, relate to a variety of digital assets, including cryptocurrencies, NFTs, and DeFi. Using QQR, quantile Granger, and the QC approach, we explore the impact of physical and transition risks on the returns of cryptocurrencies, NFTs, and DeFi. The results show an asymmetric impact of climate-related risks on cryptocurrencies, NFTs, and DeFi, where higher (lower) climate-related risks increase (decrease) their returns. The asymmetric impact of climate risks on digital assets demonstrates the necessity of effective risk management techniques that consider the impact of physical and transition risks on underlying assets, investor confidence, and market liquidity. In addition, the environmental impacts of cryptocurrencies, NFTs, and DeFi protocols highlight the significance of sustainability within the digital asset industry. As the industry continues to grow and evolve, it is imperative that businesses and users adopt sustainable practices and technologies that reduce carbon emissions and energy consumption.

The asymmetric impacts of climate-related risks on cryptocurrencies, NFTs, and DeFi can be explained by the unique characteristics of these digital assets and the nature of climate risks. Cryptocurrencies, NFTs, and DeFi protocols are all digital assets that are not tied to physical assets, making them highly susceptible to market volatility and liquidity risks. Climate risks, on the other hand, are physical and transition risks that arise from the impact of climate change on physical infrastructure and economic systems. The asymmetric impact is because the risk exposure of these digital assets to climate risks is not uniform. Some digital assets may be more exposed to climate risks than others, depending on their underlying asset classes and the industries in which they operate. For example, a DeFi protocol that is heavily invested in the fossil fuel industry may be more vulnerable to transition risks than a protocol that is focused on renewable energy investments. Furthermore, the impacts of climate risks on these digital assets may be amplified by the interconnectedness of the financial system. Climate risks can result in widespread economic disruption, leading to a decline in investor confidence and market liquidity. This in turn can lead to systemic risk that affects multiple digital assets and financial institutions.

For regulators, policymakers, and investors, our findings have significant policy implications. Regulators must recognize the increasing interconnection between climate-related risks and digital assets, as evidenced by the findings of this study. The asymmetric impact of climate risks indicates the need for tailored regulatory frameworks that address the specific vulnerabilities of these emerging markets. Hence, regulators should consider integrating climate risk disclosures into existing frameworks for digital asset reporting, ensuring that market participants are aware of both the physical and transition risks. Moreover, there is a need to develop standards for the sustainable operation of digital assets, including encouraging the adoption of low-carbon technologies within the industry.

As this study highlights the potential asymmetric effects of climate risks on digital assets, it is clear that policymakers must advocate for policies that incentivize sustainability within the digital finance sector. This could involve providing support for innovation in relation to green blockchain technologies or encouraging the development of DeFi protocols that focus on renewable energy investments, mitigating the exposure to transition risks associated with carbon-intensive industries. Policymakers should also ensure that adequate taxation policies or carbon offsetting schemes are in place to hold digital asset projects accountable for their environmental impacts, while also fostering the development of energy-efficient blockchain infrastructure. Additionally, policymakers should encourage industry collaboration to promote transparency in terms of environmental impact reporting and support the implementation of carbon footprint tracking tools for digital assets. Through taking these proactive steps, policymakers can help reduce the sector's environmental impact while bolstering its long-term viability.

For investors, this study provides crucial insights into the risk exposure of digital assets to climate risks. The asymmetric impact of climate risks means that investors must be more vigilant when assessing the potential risk of their portfolios, especially in volatile market conditions influenced by climate change. Hence, investors should incorporate climate risk analysis into their decision-making processes by using tools that specifically capture the impacts of both physical and transition risks on digital assets. Furthermore, better understanding the interdependencies between climate risks and digital asset valuations can help investors make more informed choices, particularly in terms of identifying assets that may be more vulnerable to climate-induced disruptions. Here, the growing importance of sustainability in digital asset markets presents an opportunity for investors to align their portfolios with both assets and projects that are committed to reducing their carbon footprints, thus contributing to achieving the wider goals of environmental stewardship. In so doing, investors can not only protect themselves from potential climate-related losses but also position themselves to benefit from the increasing demand for sustainable and resilient digital assets.

CRediT authorship contribution statement

Bhuiyan Rubaiyat Ahsan: Writing – review & editing, Resources, Investigation. **Abakah Emmanuel Joel Aikins:** Writing – review & editing, Visualization, Supervision, Project administration. **Abdullah Mohammad:** Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Lee Chi-Chuan:** Writing – review & editing, Investigation, Funding acquisition, Conceptualization. **Adeabah David:** Writing – original draft, Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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Data availability

Data will be made available on request.

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